

LA-UR-21-27985

Approved for public release; distribution is unlimited.

Title: Uncertainty Quantification in High Explosives Equations of State

Author(s): Lordi, Noah Perry
Lindbloom, Jonathan Tobias

Intended for: Report

Issued: 2021-08-10

Disclaimer:

Los Alamos National Laboratory, an affirmative action/equal opportunity employer, is operated by Triad National Security, LLC for the National Nuclear Security Administration of U.S. Department of Energy under contract 89233218CNA000001. By approving this article, the publisher recognizes that the U.S. Government retains nonexclusive, royalty-free license to publish or reproduce the published form of this contribution, or to allow others to do so, for U.S. Government purposes. Los Alamos National Laboratory requests that the publisher identify this article as work performed under the auspices of the U.S. Department of Energy. Los Alamos National Laboratory strongly supports academic freedom and a researcher's right to publish; as an institution, however, the Laboratory does not endorse the viewpoint of a publication or guarantee its technical correctness.

Uncertainty Quantification in High Explosives Equations of State

Students: Noah Lordi & Jonathan Lindbloom

Mentors: Jeff Leiding, Stephen Andrews, Chris Ticknor

XCP Computational Physics Student Summer Workshop

Final Presentations

August 10-12, 2021

Noah Lordi

Education

- Graduated Santa Clara University in 2020 with a bachelors in Physics and Mathematics
- Currently 2nd year Ph.D student in Physics at CU Boulder

Research Interests

- Quantum information theory
- Quantum Computation
- Quantum materials research



Jonathan Lindbloom

Education

- Graduated SMU '21 with Mathematics B.S., Finance B.B.A.
- Incoming Applied Mathematics doctoral student at Dartmouth College

Research Interests

- Inverse problems + UQ
- Probabilistic machine learning
- Surrogate models



SMU®

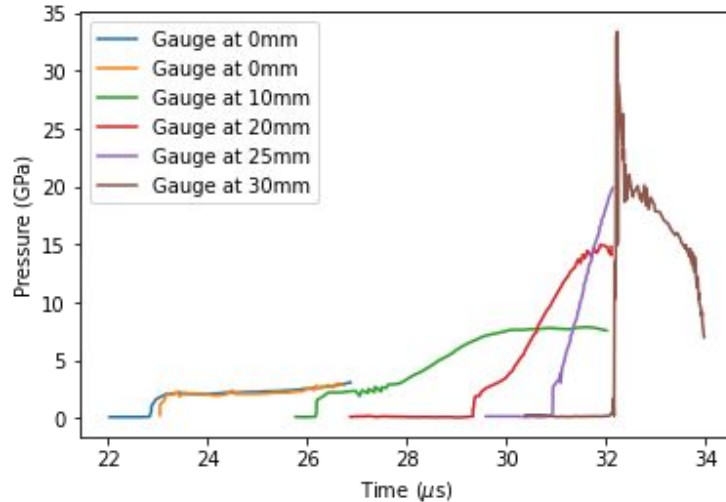


Simulation Validation and Uncertainty Quantification

- In order to fit models to data, we need a way to simulate the data given a model
- Our projects involved simulators for the Manganin gauge experiment and for cylinder tests, which we use to calibrate models to experiments
- We call the parameters we seek to optimize the degrees of freedom (DOF)
- We use a Bayesian approach with its associated UQ benefits

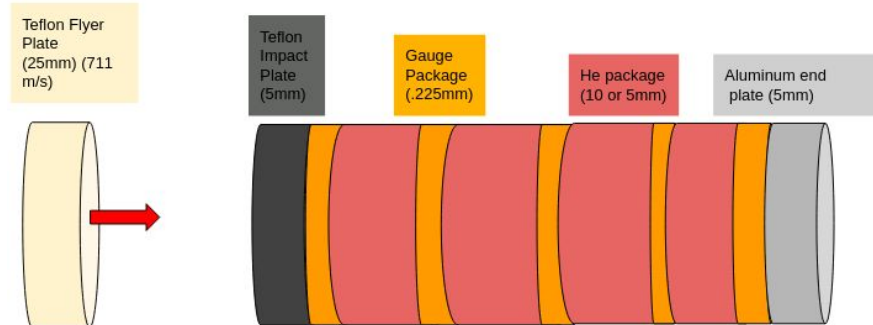
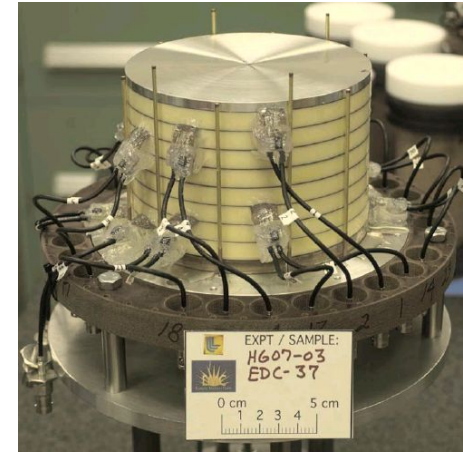
$$P(\theta|\mathcal{Y}) \propto P(\mathcal{Y}|\theta)P(\theta)$$

The Manganin Gauge Project



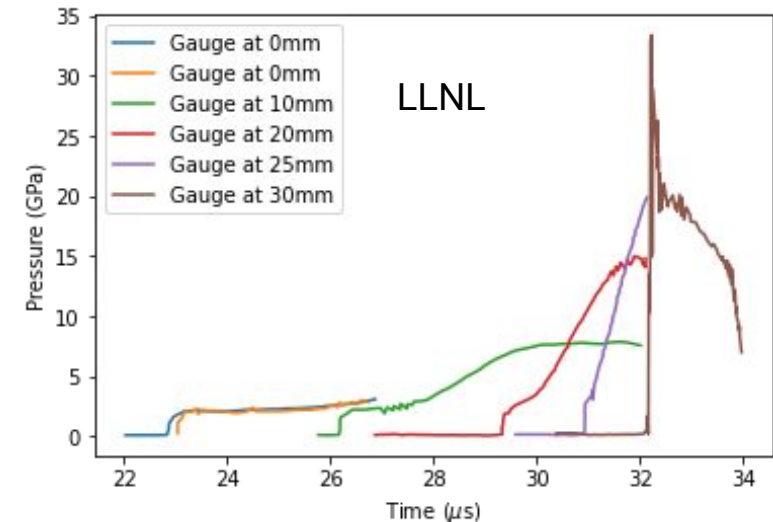
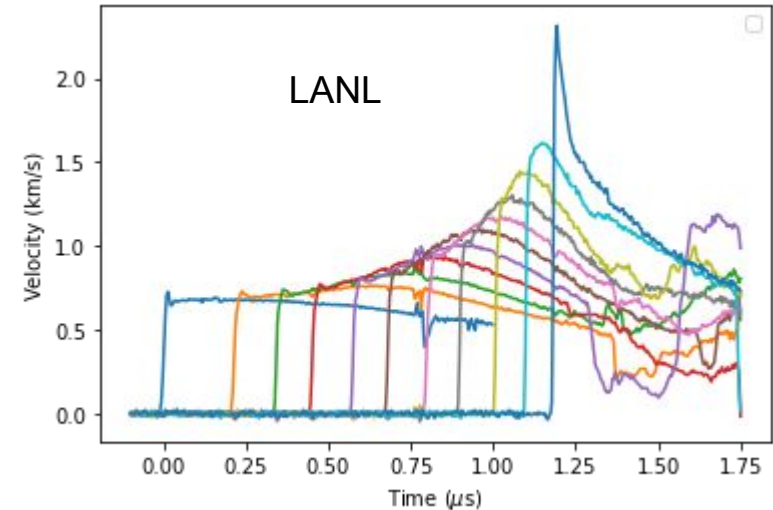
Experimental Setup

- Flyer plate impacts the setup to create an initial shock
- Shock Propagates at more than 3 km/s
- GPa pressure scales and microsecond time scales
- Supersonic shockwaves at detonation



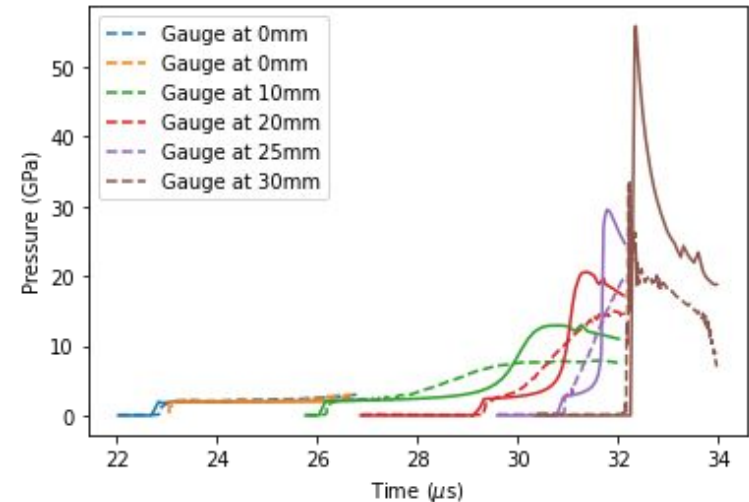
Experimental Data

- This problem is very difficult to simulate
- Embedded gauge data from LANL is well studied
 - Historically hard to simulate
- LLNL has also run manganin gauge experiments
 - LLNL embeds gauges in teflon
 - Nontrivial wave-dynamics
- Want to incorporate LLNL data for EOS calibration and validation



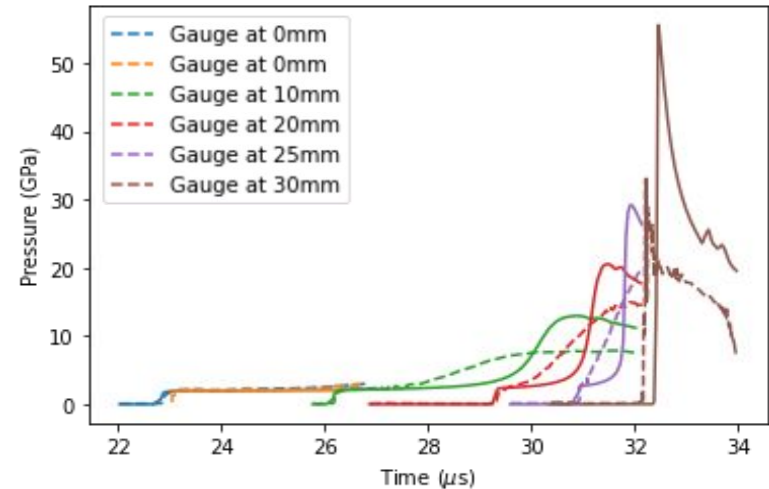
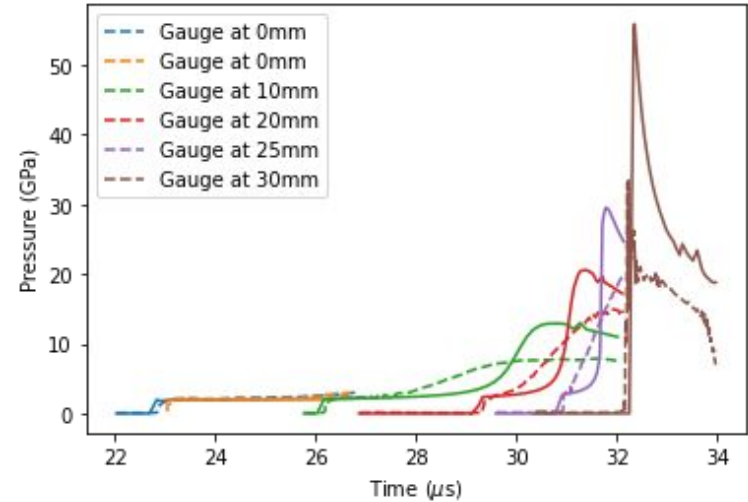
Direct Simulation Efforts

- Used a one dimensional unstable lagrangian (ODUL) solver within the ARISEE hydrocode
- Modeled the PBX9501 HE as a reactive flow
 - 26 parameters, 6 degrees of freedom (DOF)
- Initial values informed by previous research²
- Gets a lot correct
 - Predicts detonation



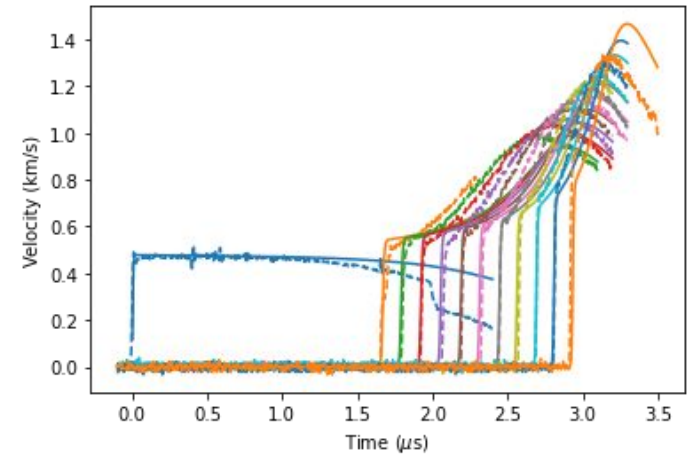
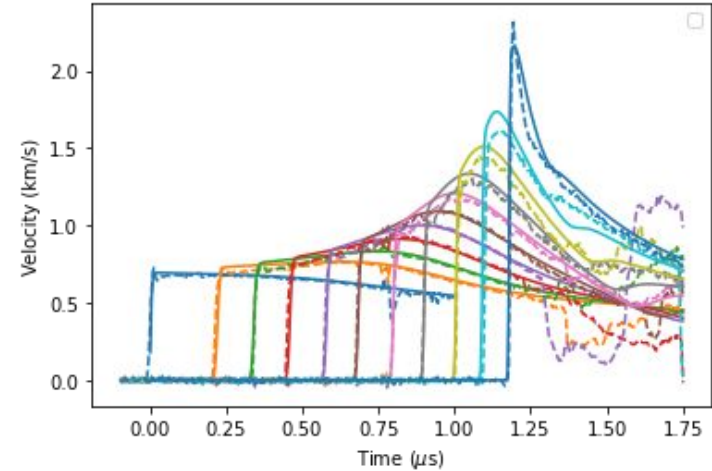
Simulation Optimization

- After one iteration of optimization we encounter a local minima
- Good qualitative agreement between simulation and experiment
- Want to compare to the LANL experiments



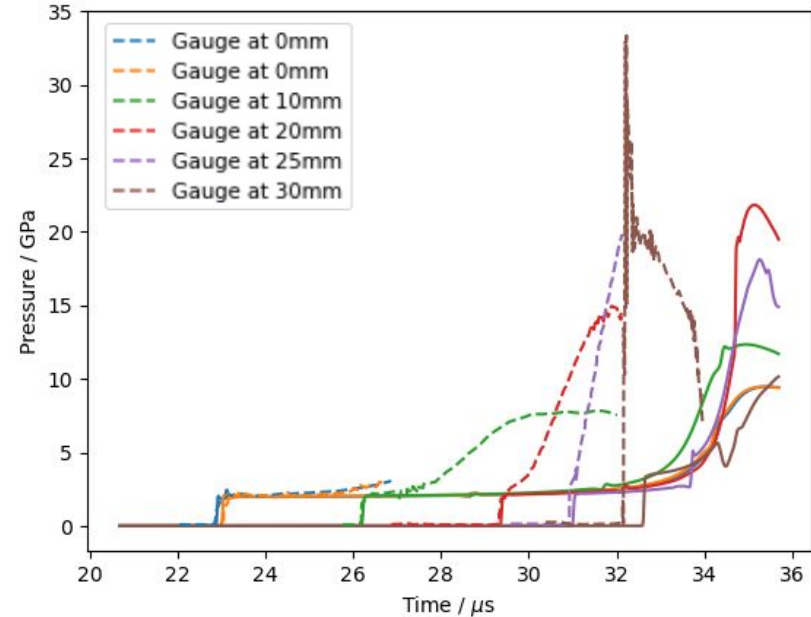
Comparing LANL and LLNL data

- Use the optimization scheme on the LANL experiments
 - Very good agreement
- Simultaneously optimize multiple experiments
- Thinner gauges and simpler wave mechanics
 - We trust this data
- These two LANL experiments are consistent
 - use same DOFs

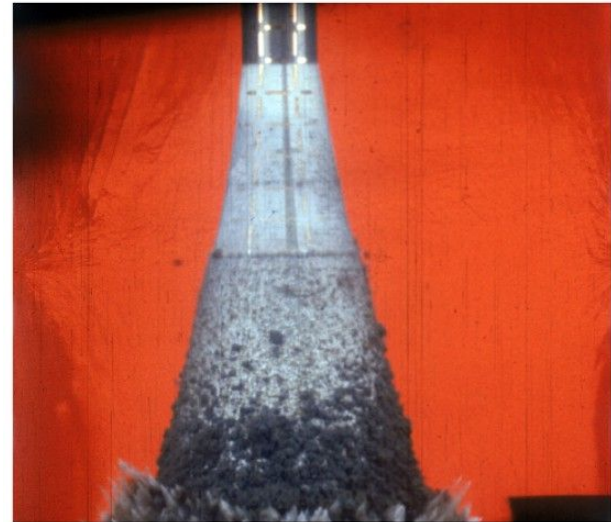
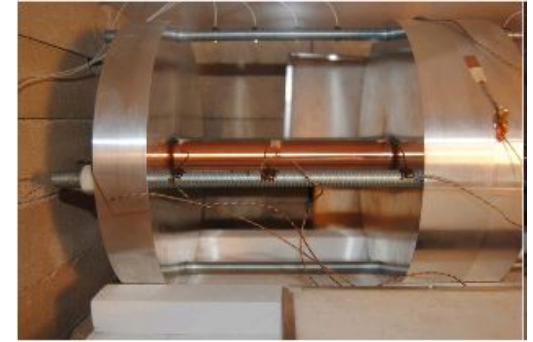
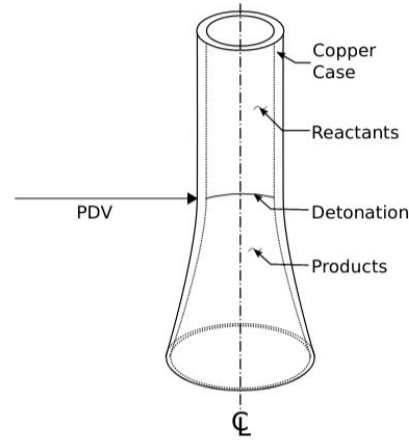
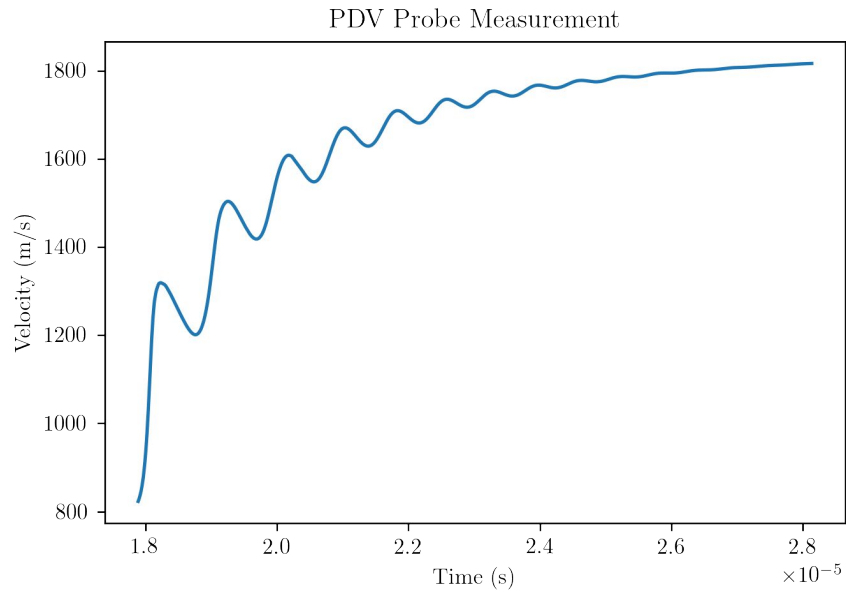


Validating the LLNL Data

- Using the DOFS from our previous optimizations
- LANL and LLNL data appear to be inconsistent
 - Different DOFS fit each experiment
 - Possible there is missing physics
- We are able to fit the LLNL data, but not as well as the LANL data



The Cylinder Test Project

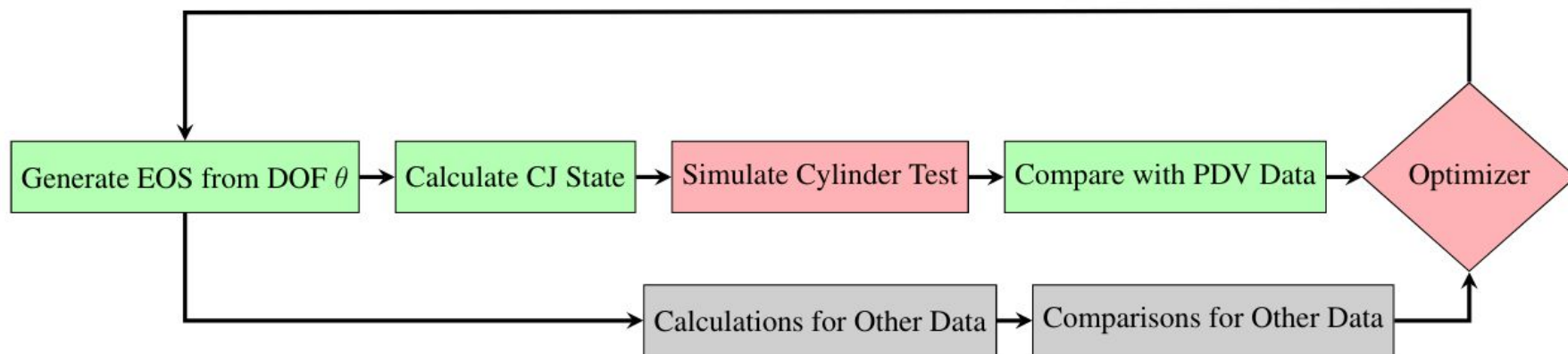


The CJ State

- The CJ state of a HE is the thermodynamic state at which the shock wave is sonic and the detonation is self-sustaining
- The CJ isentrope is the locus of thermodynamic states that the HE expands on during an explosion
- The CJ isentrope passes through the CJ state
- We cannot measure the entire CJ state directly, instead we view complicated functions of the CJ state (e.g. PDV probe data)

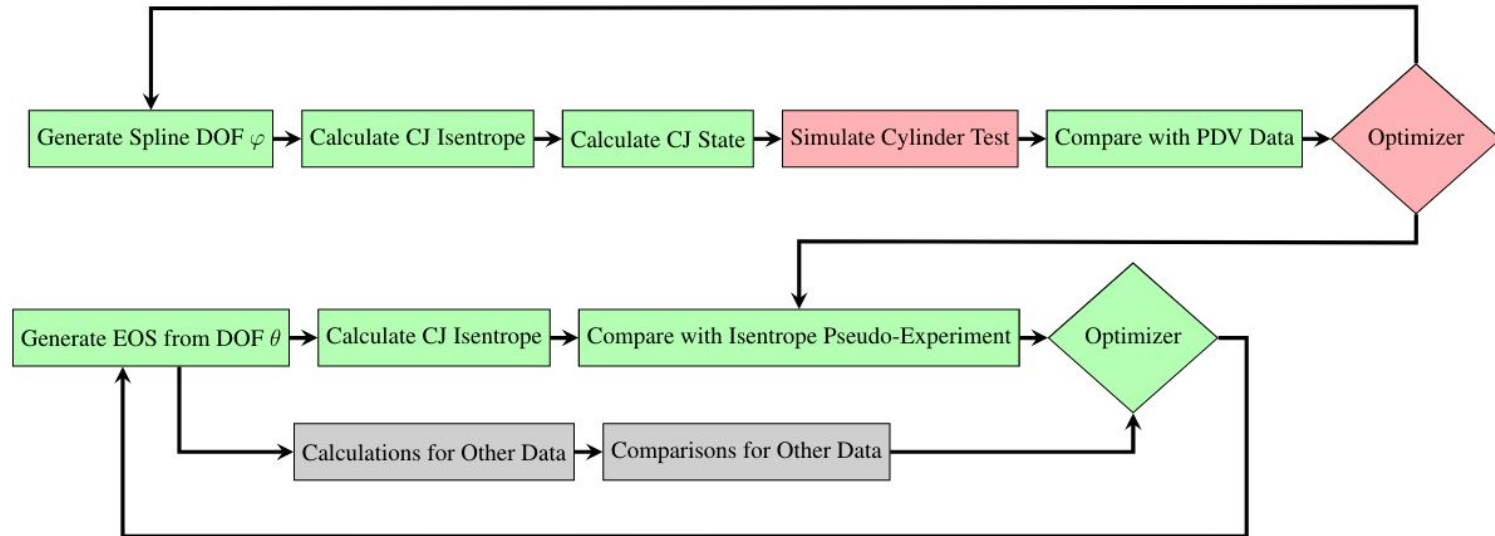
Simulating Cylinder Tests

- Running cylinder test simulations takes a long time (~45 minutes)
- Optimizers run many simulations to explore the parameter space (~2 days)
- Comparing errors in thermodynamic quantities is fast (< 1 second)
- Can we somehow avoid these simulations by extracting the information they contain upfront?



Proposed Workflow

- Cylinder tests inform the CJ isentrope
- Use a Gaussian process spline method to learn the CJ isentrope with uncertainties
- Calibrate EOS to this CJ isentrope pseudo-experiment instead of PDV data

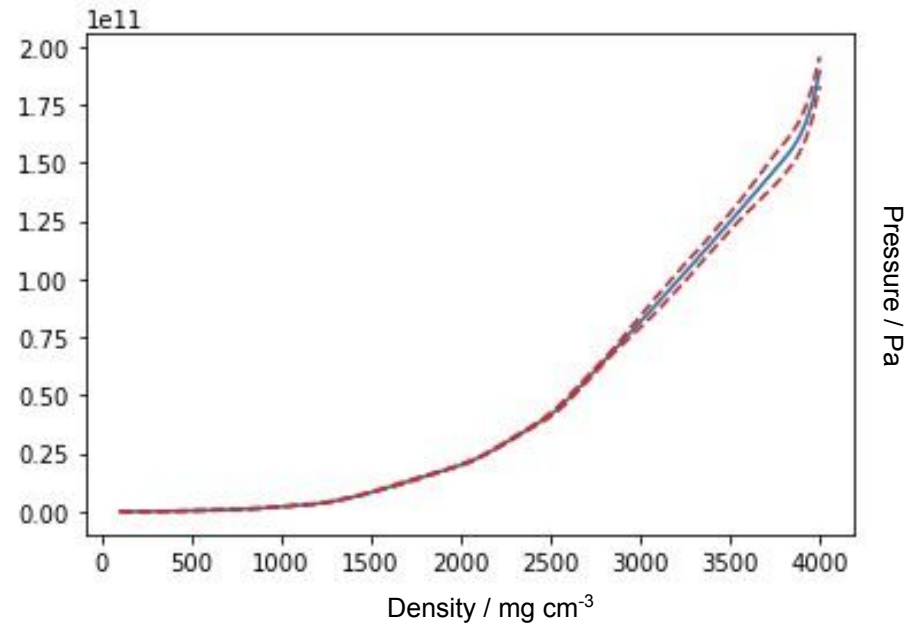
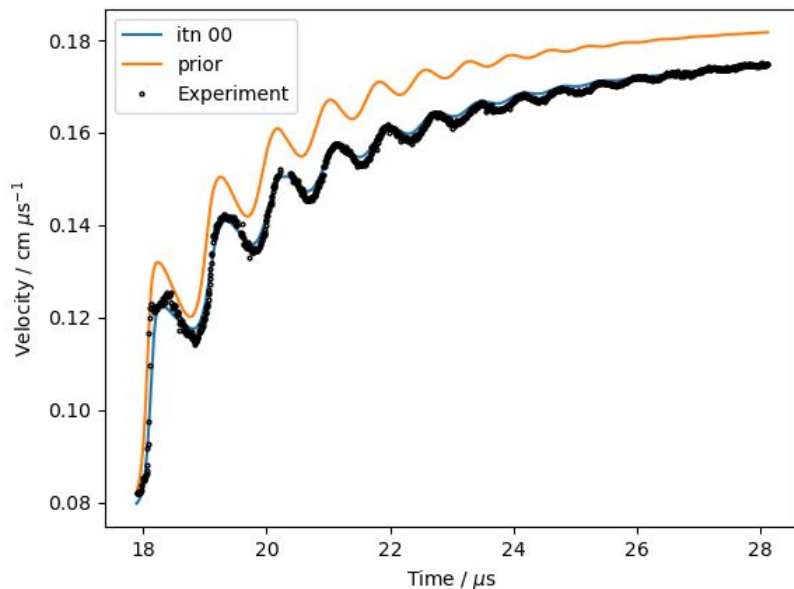


Benefits

- Fitting an EOS model becomes very fast (< 1 minute, instead of days) and permits uncertainty quantification for parameters and quantities of interest
- The learned CJ isentrope is agnostic towards any functional form
- We can fit many different parametric EOS models to the same CJ isentrope pseudo-experiment
- In principal we never need to run the cylinder test simulation again

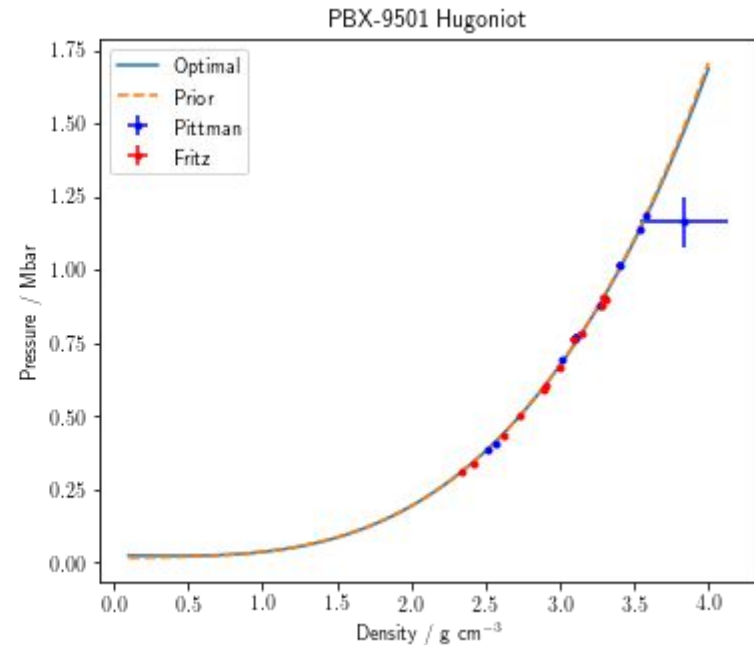
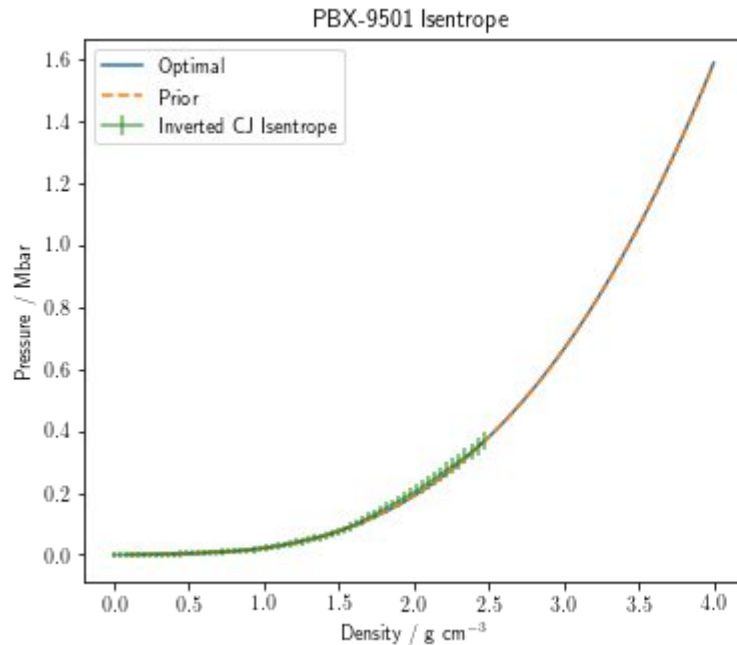
Step 1: Invert the CJ Isentrope

- Simulate many cylinder tests using varying proposal isentrope curves



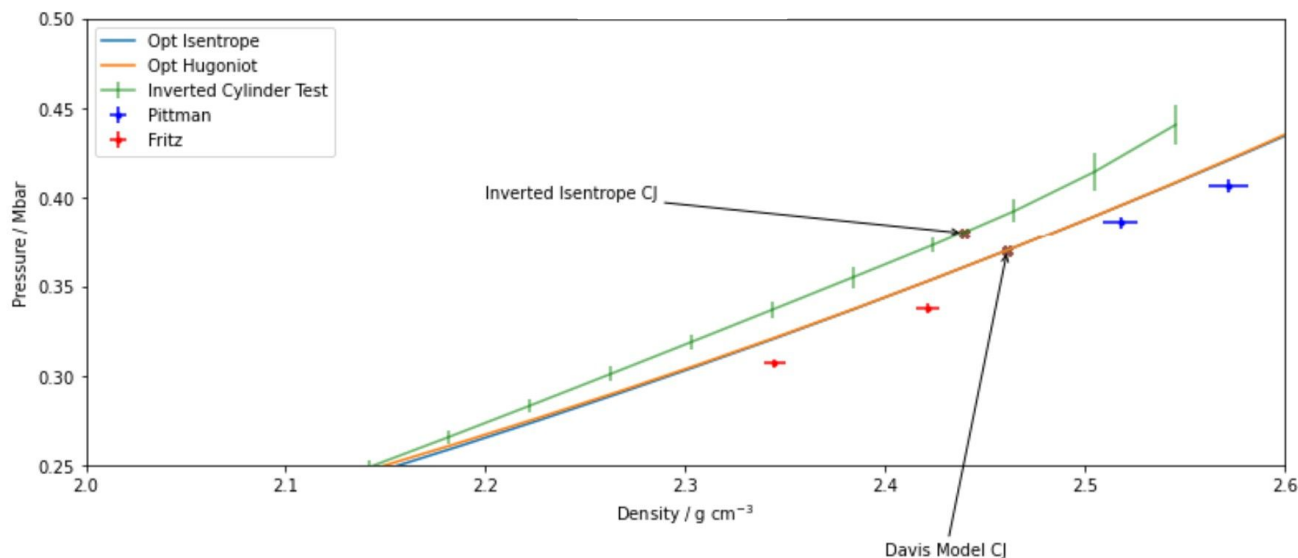
Step 2: Invert the EOS Model

- We use the Davis Products EOS
- Fit to CJ isentrope pseudo-experiment and overdriven Hugoniot data

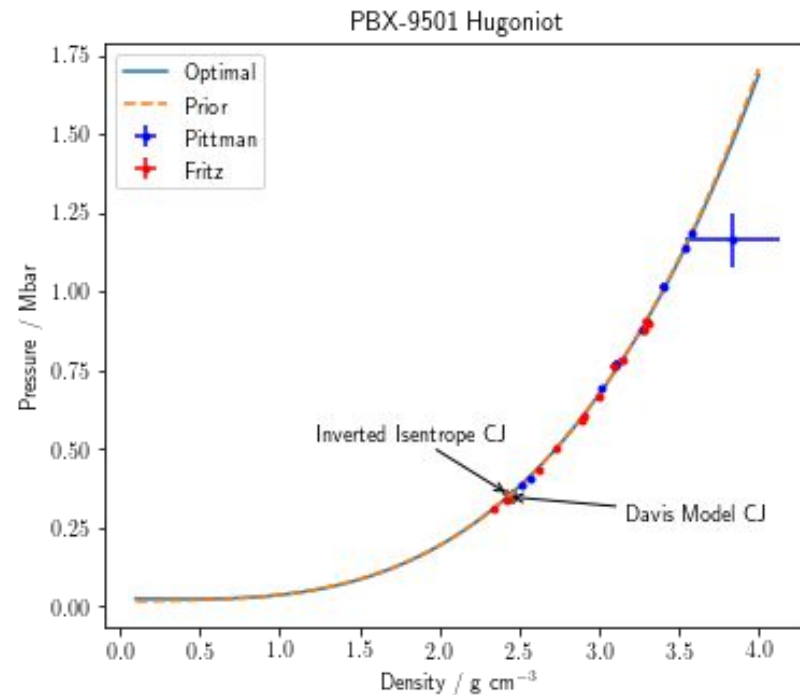
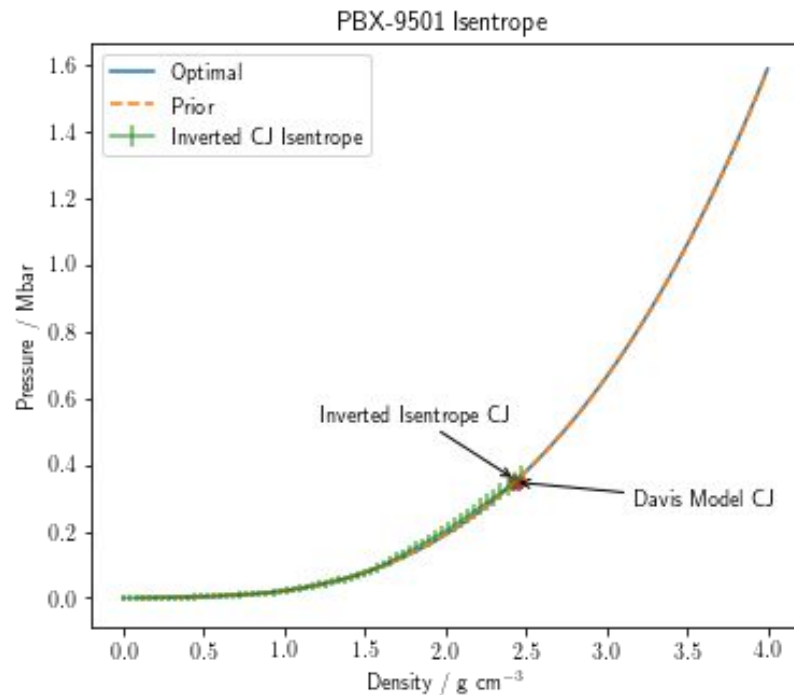


Conflicting CJ States

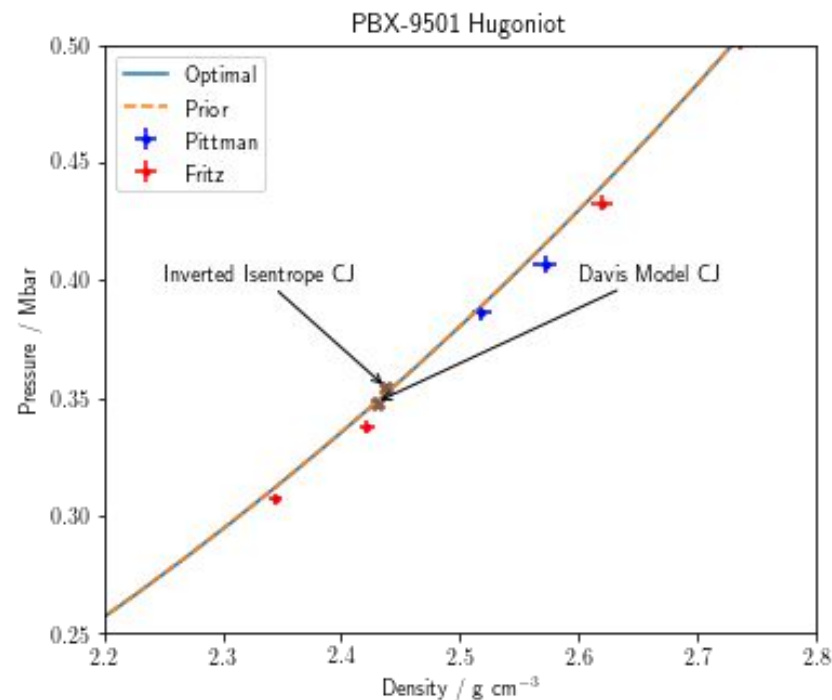
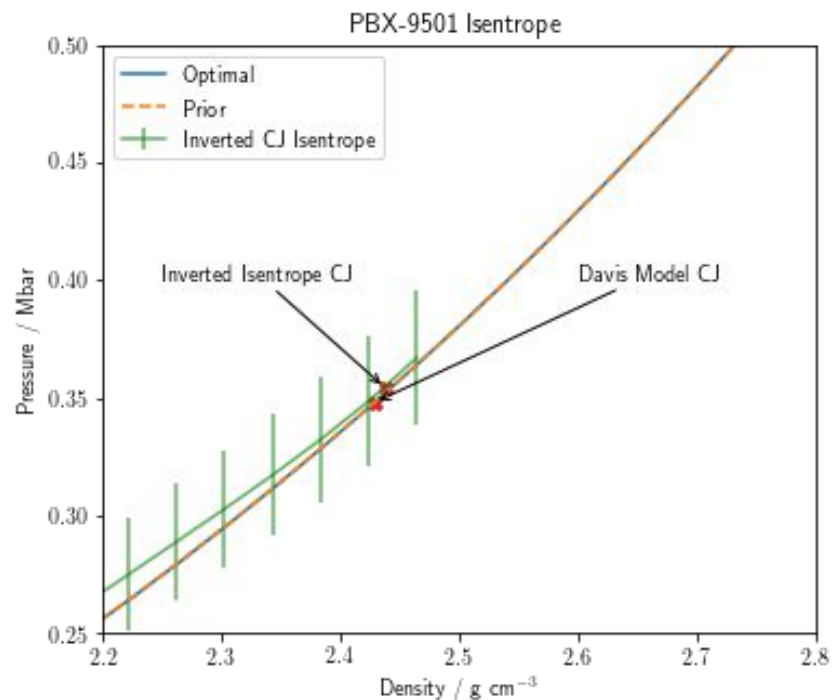
- Under this method, both the isentrope inversion and the EOS model infer a distribution over CJ states for the HE
- We remedy this by constraining the isentrope inversion by the observed detonation velocity, which was also measured during the cylinder test



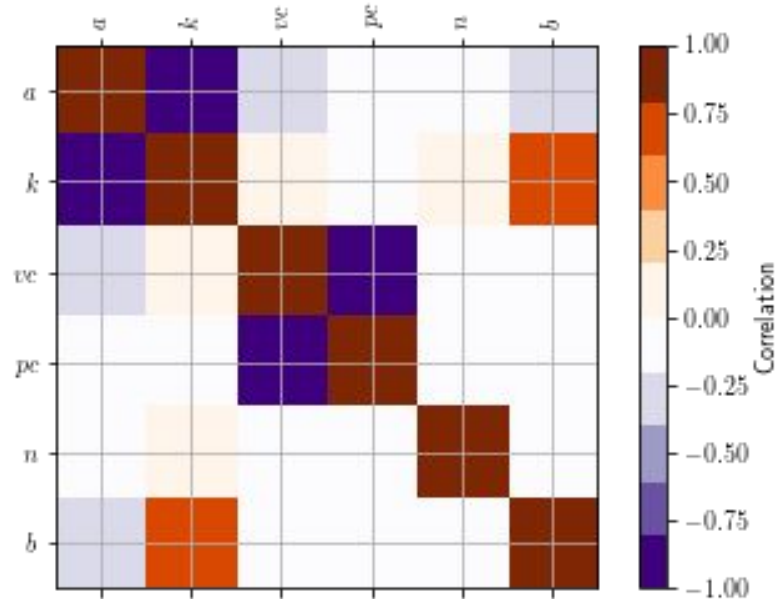
Resulting Davis Products EOS Fit



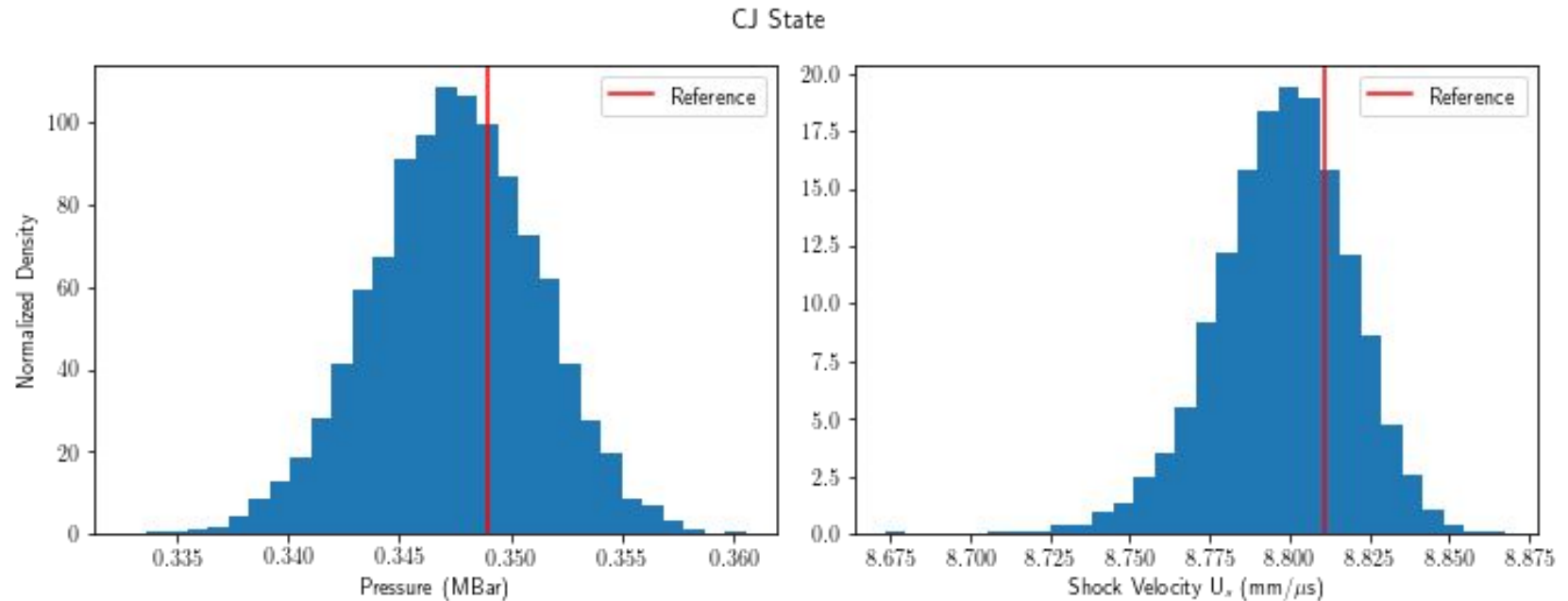
Resulting Davis Products EOS Fit



Uncertainty Quantification on Model DOF



Uncertainty Quantification on Model DOF



Conclusion

- The technique for inverting the CJ isentrope works well
- This introduces tension from two models inferring the CJ state independently
- Care must be taken to address conflicting CJ states
- The key benefit is that fitting EOS models downstream becomes fast
- Future work can explore the consistency of the cylinder test inversion across probes, shots, and experiments